Lossless and Lossy Compression of DICOM images With Scalable ROI

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Abstract
Most of the commercial medical image viewers do not provide scalability in image compression and/or encoding/decoding of region of interest (ROI). This paper discusses a medical application that contains a viewer for digital imaging and communications in medicine (DICOM) images as a core module. The proposed application enables scalable wavelet-based compression, retrieval, and decompression of DICOM medical images and also supports ROI coding/decoding. Furthermore, the presented application is appropriate for use by mobile devices activated in a heterogeneous network. The methodology involves extracting a given DICOM image into two segments, compressing the region of interest with a lossless, quality sustaining compression scheme like JPEG2000, compressing the non-important regions (background, et al.,) with an algorithm that has a very high compression ratio and that does not focus on quality (SPIHT). With this type of the compression work, energy efficiency is achieved and after respective reconstructions, the outputs are integrated and combined with the output from a texture based edge detector. Thus the required targets are attained and texture information is preserved.

Keywords:
ROI, DICOM, SPIHT, JPEG, NONROI, PSNR, MSE, CR

Introduction

To meet the demand for high speed transmission of image; efficient image storage, remote treatment and an efficient image compression technique is essential. Wavelet theory has great potential in medical image compression. In the diagnosis of medical images, the significant part(ROI) is separated and the region of less significance are compressed using Discrete Wavelet Transform and finally Huffman coding is applied to the resultant image to get the compressed image. Advanced Medical imaging applications require storage of large quantities of digitized clinical data and due to the constrained requirements of medical data archiving, compression is adapted in most of the storage and transmission applications. There are two categories of compression: Lossy and lossless methods. Based on the system requirement any one of the methods is employed. Lossless compression ensures complete data fidelity after the reconstruction, and yet the compression ratio is limited in general from 2:1 to 3:1. The application of lossy techniques results in information loss to some degree, but it can provide more than 10:1 compression ratio with little perceptible difference between reconstructed and original images. The method proposed in this paper has been programmed and simulated using the MATLAB software.

Among the existing compression schemes, transform coding is one of the most effective techniques. After the transformation, image data in spatial domain will be transformed into spectral domain to attain higher compression gain. Based on the quantization strategy, coefficients of low amplitude in the transformed domain are discarded and significant coefficients are preserved to increase the CR without inducing salient distortion. Further employment of coding technique yields lesser number of bits per pixel. This paper discusses a medical application that contains a viewer for digital imaging and communications in medicine (DICOM) images as a core module.

The proposed application enables scalable wavelet-based compression, retrieval, and decompression of DICOM medical images and also supports ROI coding/decoding. Various types of mobile devices (e.g., Pocket personal computers, personal digital assistants (PDAs), etc.) support applications used by medical personnel for retrieving and examining patient data [1], [2]. Most of these applications deal with medical images, such as computed tomography (CT) scans, computed radiography (CR) scans, and magnetic resonance (MR) images, stored in picture archiving and communication systems (PACS) and/or hospital information systems (HIS). The visual quality of the medical images/scans is required to be high in order to ensure correct and efficient assessment resulting in correct diagnosis. In this context, a mobile device has to handle medical images of significant sizes, while also taking into account its own limitations concerning memory and processing resources. For reducing the size of medical images, the discrete wavelet transform has been widely used in various applications for medical image manipulation. Indicative examples include wavelet-based applications for medical images compression [3], [4] for MR and ultrasound images denoising [5], [6], and for medical images features' extraction [7], [8].A plethora of medical image file

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viewers can be found in international literature (for a collection of them, see [9]). Most of them include functionalities that allow image and header information extraction (in case of DICOM compliant images),as well as partial image manipulation. The DICOM standard launched by the National Electrical Manufacturers Association (NEMA) facilitates the distribution and viewing of medical images. DICOM defines a special file format that contains a header (that stores information about the patient's name, the type of image, image dimensions, etc.), and the rest of the image data. Section (2) focuses DICOM images; Section (3) emphasizes on existing systems & proposed system. Section (4) includes results and discussion.

2. DICOM Images

DICOM is a standard for handling, storing, printing, and transmitting information in medical imaging. It includes a file format definition and a network communications protocol. The communication protocol is an application protocol that uses TCP/IP to communicate between systems. DICOM files can be exchanged between two entities that are capable of receiving image and patient data in DICOM format. NEMA holds the copyright of this standard.

DICOM enables the integration of scanners, servers, workstations, printers, and network hardware from multiple manufacturers into a picture archiving and communication system (PACS). The different devices come with DICOM conformance statements which clearly state the DICOM classes they support. DICOM has been widely adopted by hospitals and is making inroads in smaller applications like dentists' and doctors' offices. DICOM is the third version of a standard developed by American College of Radiology (ACR) and NEMA. In the beginning of the 1980s it was almost impossible for anyone other than manufacturers of CT or MR imaging devices to decode the images that the machines generated. Radiologists wanted to use the images for dose-planning for radiation therapy. ACR and NEMA joined forces and formed a standard committee in 1983. Their first standard, ACR/NEMA 300, was released in 1985. Very soon after its release, it became clear that improvements were needed; the text was vague and had internal contradictions. In 1992 by the US Army and Air Force as part of the MDIS (Medical Diagnostic Imaging Support) program run out of Ft. Detrick, Maryland. Loral Aerospace and Siemens Medical Systems led a consortium of companies in deploying the first US military PACS at all major Army and Air Force medical treatment facilities and teleradiology nodes at a large number of US military clinics. DeJarnette Research Systems and Merge Technologies provided the modality gateway interfaces from third party imaging modalities to the Siemens SPI network. The Veterans Administration and the Navy also purchased systems off this contract.

3. Existing systems & Proposed System

Most of the existing systems follow the technique of observing an image, figuring out the ROI and then use lossless (JPEG 2000) or lossless (SPIHT) compression techniques to achieve the result. A brief background about JPEG2000 & SPIHT is discussed here.

Keynotes on JPEG2000

The JPEG2000 standard provides a set of features that are of importance to many high-end and emerging applications by taking advantage of new technologies. It addresses areas where current standards fail to produce the best quality or performance and provides capabilities to markets that currently do not use compression. The markets and applications better served by the JPEG2000 standard are internet, color facsimile, printing, scanning, digital photography, remote sensing, mobile, and medical image. Each application area imposes some requirements that the standard should fulfill. Some of the most important features that this standard should possess are the following [10].

* Improved compression efficiency
* Lossy to lossless compression
* Multiple resolution representation
* Region of interest (ROI) coding
* Random code-stream access and processing

Keynotes on SPIHT

Set partitioning in hierarchical trees (SPIHT), proposed by Said and Pearlman [17], is one of the most efficient image compression algorithms. The effectiveness of the SPIHT algorithm originates from the efficient subset partitioning and the compact form of the significance information. The SPIHT algorithm defines spatial orientation trees, sets of coordinates, and recursive set partitioning rules [17]. The algorithm is composed of two passes: a sorting pass and a refinement pass. It is implemented by alternately scanning three ordered lists: list of insignificant sets (LIS), list of insignificant pixels (LIP), and list of significant pixels (LSP). The LIS and LIP represent the individual and sets of coordinates, respectively, for wavelet coefficients that are less than a threshold. During the sorting pass the significance of LIP and LIS are tested, followed by removal (as appropriate) to LSP and set splitting operations to maintain the insignificance property of the lists. In the refinement pass, the th most significant bits in the LSP, which contains the coordinates of the significant pixels, are scanned and output. The SPIHT algorithm reduces the threshold and repeats the two passes until the bit budget is met. Recently, many modifications have been made to the SPIHT algorithm, SPIHT-based coding representing a very active area of research. For example, Pearlman et al. proposed a set-partitioning embedded block coding algorithm [16] to extend SPIHT to block-based image coding. SPIHT has also been modified [6] for real-time image and video transmission using optimal error protection. In addition, in [12], an efficient color image compression algorithm has been proposed based on the SPIHT algorithm.

A major drawback, however, of the JPEG2000 standard is the fact that it does not support lossy-to-lossless ROI compression. In [11], a lossy-to-lossless RO I compression scheme based on SPIHT [12] and embedded block coding with optimized truncation (EBCOT) [13] is proposed. The input images are segmented into the object of interest and background and a chain code-based shape coding scheme [14] is used to code the ROI's shape information. Then, the critically sampled shape-adaptive integer wavelet transforms [15] are performed on the object and background image separately to facilitate lossy-to-lossless coding. Two alternative ROI wavelet-based coding methods with application to digital mammography are proposed by Penedo et al. in [16]. The EZW algorithm is applied to the resulting wavelet coefficients to refine and encode the most significant ones. Compression scalability is also supported in the HS-SPIHT [17], where the SPIHT is enhanced to support spatial scalability providing a bit stream that can be easily adapted (reordered) to given bandwidth and resolution requirements by a simple transcoder. Another approach using wavelet localization for ROI-specific scalable compression is presented in [17]. The wavelet coefficients at each level are correlated to weighting factors allowing scalability based on the received Peak SNR (PSNR). Apart from compression scalability for the whole image or a specific ROI, additional rate scalability can be introduced during network transmission of the image. The latter technique, however, applies mostly on cases of video transmission

The proposed application adopts the Lossy compression is performed by multiplexing a small number of wavelet coefficients (consisting of the base layer and a few of additional layers for enhancement). Thus, a large number of layers are discarded, resulting in statistically higher compression results concerning the file size. However, lossy medical image compression is considered to be unacceptable for performing diagnosis in most of imaging applications due to quality degradation. Therefore, in order to improve the diagnostic value of lossy compressed images, the ROI coding concept is introduced in the proposed application to improve the quality in specific regions of interest only by applying lossless or low compression in these regions, maintaining the high compression in none of the interest regions of the image.

The wavelet-based ROI coding algorithm implemented in the proposed application is depicted in Fig. 1 (block diagram) ROI and on the region of non-region of interest (NONROI) are quantized with different step sizes.

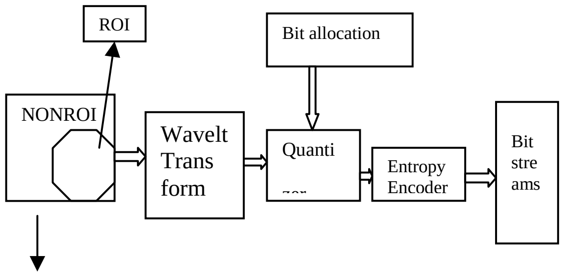

Fig 1. ROI Coding System

An important characteristic in all medical images is that it can be classified into two areas easily. Two areas are to be part that is subject to diagnosing the images. So the first step in the paper is segmenting the image into two regions. One approach is suggested for this is the selection of the region of interest by hand and then superimposing the selected pixel matrix on an MXN matrix of zeroes, where M and N refer to the number of horizontal and vertical pixels in the image respectively. The background is left as such with zero values for the selected.

A MATLAB-code has been developed and several experiments have been carried out in different types of images selected from DICOM database. Few cases are discussed here. Initially an image is scalably selected with ROI & NONROI. The corresponding area is masked and compressed using Huffman encoding. For ROI, data is saved before the decomposition using DWT then NON-ROI is compressed using SPIHT encoding and the data is saved before compression, finally its decomposed using DWT. The decompression of NONROI & ROI are carried out using SPIHT & Huffman decoding respectively

Huffman coding is one of the lossless and entropy coding. This is effectively used for reliable transmission of high quality images through wireless communication channels especially for real-time applications. The proposed method is used to achieve efficient compression that maintains the good image quality without increasing the transmission bandwidth, which also builds Lossless Encoder & Decoder Channel. Entropy is the number of bits needed to encode the data and Huffman, Variable Length, Arithmetic, Run Length are some of its techniques, In our compression technique we are applying Huffman Encoding & Decoding technique. SPIHT encoding and decoding methods are already explained under the work carried out so for. Furthermore, Peak signal to noise ratio (PSNR), Mean square error (MSE) and Compression ratio (CR) are tabulated for different cases. The average encryption and decryption time are calculated as 0.25secs, 0.3secs respectively. In this case two methods are used to reduce the transmission time and also get the information without loss. Tables give CR, MSE and PSNR values for scalable (combined ROI and NONROI) reconstructed image. This is explained under topic Results and discussion.

4. Results and Discussion:

An important characteristic in DICOM medical images is that it can be classified in to two areas. It is to be compressed by two different lossless compression techniques. So the first step in the paper is segmenting the image into two regions. One approach is suggested for this. One is the selection of the region of interest by hand and then superimposing the selected pixel matrix on an MXN matrix of zeroes, where M and N refer to the number of horizontal and vertical pixels in the image respectively. The unselected image is remaining same it also be consider.

Simulation Results:

Results of DICOM images are tabulated and for these examples, SPHIT algorithm is used for NONROI compression and decompression. Huffman coding and decoding algorithms are used for ROI, to get lossless compression. All decoded images for each bit-rate were recovered at desired rate.

The image quality is measured in terms of PSNR and MSE.

$$PSNR = \frac{1}{N}\sum \frac{(255)^2}{(I_0[X,Y]-I_m[x,y])^2}$$

$$MSE = \sum (I_0[x,y]-I_m[x,y])^{2})/N$$

For good quality image, PSNR value should be as high as possible & MSE value should be as low as possible. Percentage of compression indicates by how much the size of the image has been reduced from its original size and it is given by:

Original file size
Compression Ratio = ---------------------
Compressed file size

Table 1. DICOM image brain-001

S.No	CR	MSE	PSNR
1.	2.04	12.71	37.08
2.	1.87	17.74	35.64
3.	2.35	19.12	36.88
4.	1.77	6.36	40.09
5.	1.97	13.32	36.88
6.	1.88	9.22	38.48
7.	2.06	14.19	36.60

It is observed that the PSNR values are varying randomly because the region of interest is scalable. Different ROI of different images are shown bellow. Original DICOM image, scalable ROI,ROI masked region and SPHIT compression of Non ROI al are shown as follows.

Dicom image brain 011 | Scalable ROI

Fig 3.Different phases of ROI coding system for DICOM image Brain-001

Table 2. DICOM image brain-012

S.No	CR	MSE	PSNR
1.	2.29	23.15	34.48
2.	1.81	11.06	37.69
3.	2.31	23.10	34.49
4.	2.38	14.34	36.56
5.	1.96	17.45	35.54
6.	1.78	17.98	34.99
7.	2.86	13.55	37.03

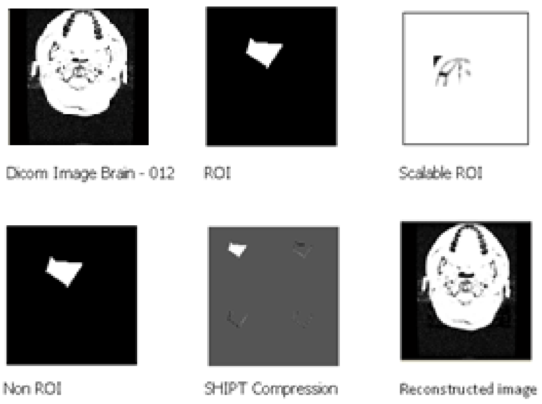

Fig 2. Different phases of ROI coding system for DICOM image Brain 012

Many images (100s of images) are compressed and few cases results are tabulated as in table 1, 2 and 3.The images corresponding too few cases are as shown depending on ROI in Fig 2 and Fig 3.

Table 3. DICOM image Brain 011

S.No	***CR***	***MSE***	***PSNR***
1.	1.77	5.53	40.69
2.	2.08	8.86	38.65
3.	2.32	11.08	37.68
4.	1.91	14.45	36.53
5.	2.21	12.81	37.05
6.	1.95	10.37	37.97
7.	1.93	9.02	38.57

Conclusion

Thus the medical image has been intelligently compressed. The method strives to achieve a high PSNR, MSE, compression time and reconstruction time as well as a high compression ratio without detoriation of the image quality. The paper also gives precise texture information to facilitate diagnosis and act as a reference line after reconstruction. The most demanding area is the need for a system which automatically extracts the region of interest and proceeds as stated above. But the pitfall is that such generalization is not of much use as ROI varies from image to image and patient to patient. Another step would be to make the edge detection adaptive and try for choice of measures that would minimize the Gaber ringing effect. The ROI can also be watermarked for security once the bit stream emerges from the encoder. This would prevent tampering of the image and also can use the memory optimally.

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